Replication of the article "Emerging Parental Gender Indifference? Sex Composition of Children and the Third Birth" From Pollard and Morgan

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INTRODUCTION

In "Emerging Parental Gender Indifference? Sex Composition of Children and the Third Birth," Pollard and Morgan's central hypothesis is that there has been a transformation in parents' preferences regarding the sex of their offspring. According to the authors, because of ruptures in the "gender system" – represented, in this article, mainly by the gendered division of labor –, parents' desire to have at least one child of each sex is declining in the US. This hypothesis opposes well-established literature pointing out that parents of two same-sex children are more likely to have (or intend to have) a third child than those that already have one child of each sex (Slone and Lee, 1983; Yamaguchi and Ferguson, 1995). To build their arguments, the authors developed some Logistic Regressions based on varying data sources, especially four cycles from the Current Population Survey (1980,1985, 1990, and 1995) and three cycles from the National Survey of Family Growth (1983, 1988, and 1995).

Their models – which had "fertility behavior" and "fertility intention" as their main independent variables– indeed present a significant decline, after 1985, in the likelihood of mothers of same-sex children having (fertility behavior) or intending to have (fertility intention) a third child. The authors aim to attribute this transformation to the aforementioned "weakening of the gender system" throughout the article. To corroborate this explanation, they attempt to falsify other plausible justifications for the phenomenon. One critical competing hypothesis for the current decline is the changes in families' social structure, particularly the increasing number of single-parent households.

To verify whether the increase in "indifference" toward the sex of children is related to "non-traditional" family structures or whether it is pervasive, the authors created a more restricted logistic regression model. Model number three, which I will replicate in this paper, has only two categories of respondents: "(1) women who were married at the birth of their second child, and (2) once-married women who were married at the birth of the first child and remained married until the third birth or censoring" (p. 607). Thus, using the author's rationale, if a decrease in the influence of the sex of the first two children on women's intention to have a third child could be detected in this group, it would mean the phenomenon is not only linked to non-traditional families.

Similar to models one and two, based on data from a larger population, model three also demonstrated a significant decline in the influence of the sex of the first two children on the intention to have a third child. Thus, the authors' hypothesis became even more robust. I will replicate and analyze model three, its assumptions, and findings in the following sections.

REPLICATION

The authors have made the codes they developed to create their logistic models widely accessible to the public. As such, the model I replicated is reasonably close to theirs. In the original model three, the authors first created five subsets from their more extensive database, keeping only the married women population and their corresponding demographic data. The five subsets - which they also grouped into a new dataset (married.ASR) - correspond to the different years the surveys were conducted, 1982, 1988, 1995, 2002, and 2006.

According to my replication, one can notice that the variable "same-sex children" ("samesexsame-sex") still has a significant influence on married women's intention to have a third child (0.48), albeit declining. Two other statistically relevant figures concern the variable "age," where increasing age significantly decreases the prospects of a third child (-0.21), and the variable "raceHispanics." In the latter, there is a rather significant influence of the gender of the first two children on the intention to have a third child (0.77), which can suggest a great ethnic-cultural difference between the Hispanic group and the others.

Finally, although less salient, it is also important to mention that there appears to be a positive relationship between the variable "educatcollege" with the intention of married women to have a third child. The data suggests that the gender of the first two children tends to influence (more) the will of women who went to college to have a third child (0.42). This information is relevant because, throughout the article, Pollard and Morgan argue that Yamaguchi and Ferguson's (1995) findings – that the influence of the sex of previous children is more substantial in highly educated women – should not prosper (Pollard and Morgan, p. 607, 2002). However, looking at Pollard and Morgan's own data, we need more caution before ruling out this hypothesis.

```
# m3: currently married sample: + demographic controls
married.ASR = ASR[which(ASR$marital == "currently married"), ]
married.1988 = NSFG1988[which(NSFG1988$marital == "currently married"), ]
married.1995 = NSFG1995[which(NSFG1995$marital == "currently married"), ]
married.1982 = NSFG1982[which(NSFG1982$marital == "currently married"), ]
married.2002 = NSFG2002[which(NSFG2002$marital == "currently married"), ]
married.2006 = NSFG2006[which(NSFG2006$marital == "currently married"), ]
m3 = glm(intent ~ samesex + as.factor(survey) + samesex * as.factor(survey) + age +
         educat + race, data = married.ASR, family = binomial(link = "logit"))
m3.1988 = glm(intent ~ samesex + age + educat + race, data = married.1988, family = bi
m3.1995 = glm(intent ~ samesex + age + educat + race, data = married.1995, family = bi
m3.1982 = glm(intent ~ samesex + age + educat + race, data = married.1982, family = bi
m3.2002 = glm(intent ~ samesex + age + educat + race, data = married.2002, family = bi
m3.2006 = glm(intent ~ samesex + age + educat + race, data = married.2006, family = bi
coef.m3 = round(c(coef(m3.1982)[2], coef(m3.1988)[2], coef(m3.1995)[2], coef(m3.2002)[
         coef(m3.2006)[2]), digits = 3)
se.m3 = round(c(sqrt(diag(vcov(m3.1982)))[2], sqrt(diag(vcov(m3.1988)))[2], sqrt(diag(vcov(m3.1988)))[2]
         \operatorname{sqrt}(\operatorname{diag}(\operatorname{vcov}(\operatorname{m3.2002})))[2], \operatorname{sqrt}(\operatorname{diag}(\operatorname{vcov}(\operatorname{m3.2006})))[2]), \operatorname{digits} = 3)
n.m3 = c(m3.1982\$df.null + 1, m3.1988\$df.null + 1, m3.1995\$df.null + 1, m3.2002\$df.null
         1, m3.2006$df.null + 1)
sig.m3 = round(c(summary(m3.1982)scoef[2, 4], summary(m3.1988)scoef[2, 4
         4], summary(m3.2002)$coef[2, 4], summary(m3.2006)$coef[2, 4]), digits = 3)
summary(m3)
##
## Call:
## glm(formula = intent ~ samesex + as.factor(survey) + samesex *
##
                as.factor(survey) + age + educat + race, family = binomial(link = "logit"),
               data = married.ASR)
##
```

```
##
## Deviance Residuals:
##
      Min
                 1Q
                     Median
                                   3Q
                                           Max
## -1.8956 -0.5416
                    -0.3617 -0.2271
                                        2.9362
##
## Coefficients:
                                         Estimate Std. Error z value Pr(>|z|)
##
## (Intercept)
                                          4.27976
                                                     0.42756 10.010 < 2e-16 ***
                                          0.48324
                                                     0.18270
                                                               2.645 0.00817 **
## samesexsame-sex
## as.factor(survey)1995
                                          0.27770
                                                     0.18358
                                                               1.513 0.13036
                                         -0.21753
                                                     0.01386 -15.697 < 2e-16 ***
## age
                                         -0.09313
                                                     0.18502 -0.503 0.61470
## educathigh school
## educatcollege
                                          0.42333
                                                     0.18561
                                                               2.281 0.02256 *
## raceblack
                                          0.05975
                                                     0.17401
                                                               0.343 0.73130
## raceHispanics
                                          0.77969
                                                     0.16832
                                                               4.632 3.62e-06 ***
## raceother
                                          0.65744
                                                     0.31965
                                                               2.057 0.03971 *
## samesexsame-sex:as.factor(survey)1995 -0.10949
                                                     0.24580 -0.445 0.65601
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 2167.5 on 2671 degrees of freedom
## Residual deviance: 1801.6 on 2662 degrees of freedom
## AIC: 1821.6
##
## Number of Fisher Scoring iterations: 5
```

Table 1: Original replication

	Initial model		
(Intercept)	4.280		
	[3.447, 5.125]		
samesexsame-sex	0.483		
	[0.127, 0.844]		
as.factor(survey)1995	0.278		
	[-0.080, 0.640]		
age	-0.218		
	[-0.245, -0.191]		
educathigh school	-0.093		
	[-0.452, 0.274]		
educatcollege	0.423		
	[0.065, 0.793]		
raceblack	0.060		
	[-0.289, 0.395]		
raceHispanics	0.780		
	[0.447, 1.107]		
raceother	0.657		
	[0.003, 1.262]		
samesexsame-sex \times as.factor(survey)1995	-0.109		
	[-0.592, 0.372]		
Num.Obs.	2672		
AIC	1821.6		
BIC	1880.5		
Log.Lik.	-900.810		
F	32.430		
RMSE	0.82		

modelsummary(list(`Initial model` = m3), statistic = "conf.int", title = "Original rep

BAYESIAN REPLICATION

As we can notice, the Bayesian replication presents results that are very similar to the original logistic regression. The most extensive variation is in the variable "raceother." In the original model, the value was 0.65, while in the Bayesian replication, this value is 0.57. The higher sensitivity to variation may be linked to a reduced

sample size for this category. However, the other variables present almost identical results in both models, corroborating how robust the authors' findings are.

```
# Bayesian model for m3
baym3 <- stan_glm(intent ~ samesex + as.factor(survey) + samesex * as.factor(survey) +
    age + educat + race, data = married.ASR, family = binomial(link = "logit"), prior
    scale = 1), seed = 12345, refresh = 0)
print(baym3)
## stan_glm
    family:
                  binomial [logit]
    formula:
                  intent ~ samesex + as.factor(survey) + samesex * as.factor(survey) +
##
       age + educat + race
##
##
    observations: 2672
##
   predictors:
                  10
##
  _____
##
                                          Median MAD_SD
## (Intercept)
                                           4.3
                                                  0.4
                                           0.5
                                                  0.2
## samesexsame-sex
## as.factor(survey)1995
                                           0.3
                                                  0.2
                                          -0.2
                                                  0.0
## age
                                                  0.2
## educathigh school
                                          -0.1
## educatcollege
                                           0.4
                                                  0.2
                                                  0.2
## raceblack
                                           0.1
## raceHispanics
                                           0.8
                                                  0.2
## raceother
                                           0.6
                                                  0.3
## samesexsame-sex:as.factor(survey)1995 -0.1
                                                  0.2
##
## ----
```

* For help interpreting the printed output see ?print.stanreg
* For info on the priors used see ?prior_summary.stanreg

```
modelsummary(list(`Initial model` = m3, `Bayesian model` = baym3), statistic = "conf.i

title = "Bayesian Replication for Model 3")
```



ALTERNATIVE SPECIFICATIONS

0.25

0.00

Another way to check how solid the results Pollard and Morgan obtained were, is to employ sensitivity checks. Therefore, in this section I propose three alternative specifications for the replicated model; in the first one I added a new variable ("catholic"), in the second I altered the original dataset removing age outliers, and in the last one, I incorporated the data into a Probit regression model. In the first specification, I decided to add the variable "catholic" because this population tends to be more prone to accepting gender norms. So, it would be interesting to see how catholic married

0.75

0.50

Table 2: Bayesian Replication for Model 3

	Initial model	Bayesian model	
(Intercept)	4.280	4.319	
` 1 /	[3.447, 5.125]	[3.492, 5.196]	
samesexsame-sex	0.483	0.469	
	[0.127, 0.844]	[0.114, 0.814]	
as.factor(survey)1995	0.278	0.259	
•	[-0.080, 0.640]	[-0.088, 0.615]	
age	-0.218	-0.218	
	[-0.245, -0.191]	[-0.243, -0.190]	
educathigh school	-0.093	-0.100	
	[-0.452, 0.274]	[-0.452, 0.246]	
educatcollege	0.423	0.419	
	[0.065, 0.793]	[0.067, 0.765]	
raceblack	0.060	0.050	
	[-0.289, 0.395]	[-0.310, 0.382]	
raceHispanics	0.780	0.758	
	[0.447, 1.107]	[0.451, 1.087]	
raceother	0.657	0.579	
	[0.003, 1.262]	[-0.024, 1.195]	
samesexsame-sex \times as.factor(survey)1995	-0.109	-0.084	
	[-0.592, 0.372]	[-0.559, 0.382]	
Num.Obs.	2672	2672	
AIC	1821.6		
BIC	1880.5		
Log.Lik.	-900.810		
F	32.430		
ELPD	-910.7		
ELPD s.e.		30.6	
LOOIC		1821.5	
LOOIC s.e.		61.2	
WAIC		1821.5	
RMSE	0.82	0.32	

women would perform. As we can notice, after adding this new variable, most results did not alter significantly compared to the initial one. This pattern corroborates the authors' argument that there is a widespread change regarding parental preference for the sex of their children, even when we observe a group that tends to be more impacted by the socialization and institutionalization of gender roles.

The only significant variations are caused by the interaction between the variable "catholic" and the variables "raceHispanic" and "raceblack." The values went from 0.78 ("raceHispanic") and 0.06 ("raceblack") in the initial specification to 0.5 and 0.18 with the new variable. These discrepancies may suggest either that there is indeed a sui generis phenomenon occurring in these groups or that the sample size was small, rendering these categories more susceptible to unrealistic variation.

In the second alternative specification, when I altered the original dataset by removing age outliers, the results found were also very similar to the initial ones. With the exception, once again, of categories involving race (now also including "raceother"). I believe that this consistent discrepancy involving the non-white racial groups points a lot more to issues in collecting this data than to any other possible underlying explanation. In that sense, Pollard and Morgan also state that they were "not able to reject the hypothesis that the sex-of-previous-children effect was the same across racial/ethnic groups (results not shown)" (p. 609), this also corroborates my assumption that there is a lack of comprehensive data associated with the racial categories.

Finally, the third scenario was utilizing an alternative model. Differently from the other two specifications, the Probit regression model displayed results that are very dissimilar when compared to the initial logistic model. However, we can notice an important pattern between the two models. There is a certain proportion between the new values and the previous ones, for the positive outcomes arising from Probit are (roughly) half of Logit's outcomes. For instance, when we observe the variable "educatcollege" it goes from 0.423 in the Logit to 0.225 in the Probit; "samesexsame-

sex" goes from 0.483 to 0.245; "raceother" goes from 0.657 to 0.375. This pattern might suggest that thefundamental relationships between the variables are maintained in the new model, even if the values are not. However, it is essential to get more information to understand further what happened in this part of the sensitivity checks mainly because the general expectation is that Logit and Probit's results usually are similar.

DISCUSSION

The results Pollard and Morgan obtained in this research are quite robust, remaining virtually unchanged both when transformed into a Bayesian regression model and when subjected to alternative specifications (apart from the Probit model). So, from a statistical data production standpoint, their outcomes are well supported. However, the authors' analysis of the social phenomenon arising from their results are less impressive and unconvincing. Even if they are correct and, since 1985, couples in the United States have been increasingly indifferent to having at least one child of

Table 3: Alternative Specifications

	Initial model	Add Catholic	Probit	Transformed
(Intercept)	4.280	4.226	2.369	5.386
· -	(0.428)	(0.431)	(0.236)	(0.516)
samesexsame-sex	0.483	0.500	0.245	0.444
	(0.183)	(0.183)	(0.099)	(0.190)
as.factor(survey)1995	0.278	0.264	0.145	0.390
- -	(0.184)	(0.185)	(0.098)	(0.190)
age	-0.218	-0.221	-0.122	-0.253
	(0.014)	(0.014)	(0.007)	(0.017)
educathigh school	-0.093	-0.120	-0.043	-0.083
<u> </u>	(0.185)	(0.186)	(0.104)	(0.202)
educatcollege	0.423	0.376	0.225	0.417
5	(0.186)	(0.187)	(0.104)	(0.199)
raceblack	0.060	0.184	0.049	0.163
	(0.174)	(0.178)	(0.095)	(0.179)
raceHispanics	0.780	0.500	0.437	0.871
-	(0.168)	(0.181)	(0.096)	(0.179)
aceother	0.657	0.627	0.375	0.581
	(0.320)	(0.323)	(0.178)	(0.338)
$samesexsame-sex \times as.factor(survey)1995$	-0.109	-0.108	-0.049	-0.206
•	(0.246)	(0.247)	(0.134)	(0.256)
catholic		0.614		
		(0.139)		
Num.Obs.	2672	2672	2672	2570
AIC	1821.6	1804.6	1815.0	1674.9
BIC	1880.5	1869.4	1873.9	1733.4
Log.Lik.	-900.810	-891.302	-897.478	-827.43
F	32.430	30.136	34.887	29.649
RMSE	0.82	0.82	0.82	0.80

each sex. This finding is not synonymous with saying that there is an increase in parents' indifference concerning the sex of their children.

To be able to more forcefully state that there is indeed an increase in parental indifference towards the sex of their children, it would also be necessary to analyze whether one sex is still more desired over the other. For example, what percentage of parents would like to have only girls or only boys, what percentage of parents who have their first child a girl decides to have a second child, and vice versa. Sticking to the influence of the sex of the first two children, it would be important to inquire how often parents of two girls decide to have a third child, is it the same as parents of two boys?

Moreover, attributing the new trend they identified to the attenuation of the "gender system" is rather one-dimensional. After all, gender norms have historically gone through shifts without it necessarily resulting from a weakening in this system. Even the advancement of women's rights – such as their incorporation into the labor market pointed out several times in the article – often goes hand in hand with increasing violence against them to reestablish and reinforce gender norms (Faludi, 2006).

To argue for some relevant weakening of the patriarchal system, it is necessary that, at the very least, women and men exhibited changes in behaviors and intentions. However, the population Pollard and Morgan investigated were only composed by women-mothers. Throughout the article, but especially when analyzing the data stemming from model number three, the authors assume a homology between the women's intentions and those of their husbands. This equation may be far from reality.

Finally, it was quite interesting to carry out this replication exercise, following the steps of others in producing their statistical

research. The most striking aspect for me was visualizing how broad a quantitative researcher's decision-making power is. From deciding which data they will incorporate or ignore, which categories they will create or dissolve, which clusters they will group or separate, which statistical model is more interesting to present their results, etc. And how all these decisions, as small as they may seem, can significantly alter their outcomes.

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